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Oslo, 6 October 2015

Barcelona Supercomputing Center
Centro Nacional de Supercomputación

EXCELENCIA SEVERO OCHOA

Predicting climate extreme events in a user-driven context

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SPECS
Seasonal-to-decadal climate Prediction for the improvement of European Climate Services

iCrea

BSC Earth Sciences Department

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EXCELENCIA SEVERO OCHOA

What

Environmental forecasting

Why

Our strength …
… research …
… operations …
… services …
… high resolution …

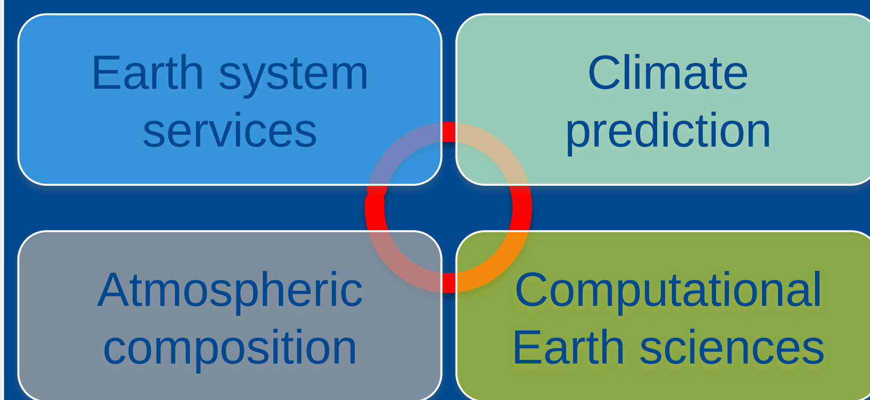
How

Develop a capability to model air quality processes from urban to global and the impacts on weather, health and ecosystems

Implement climate prediction system for subseasonal-to-decadal climate prediction

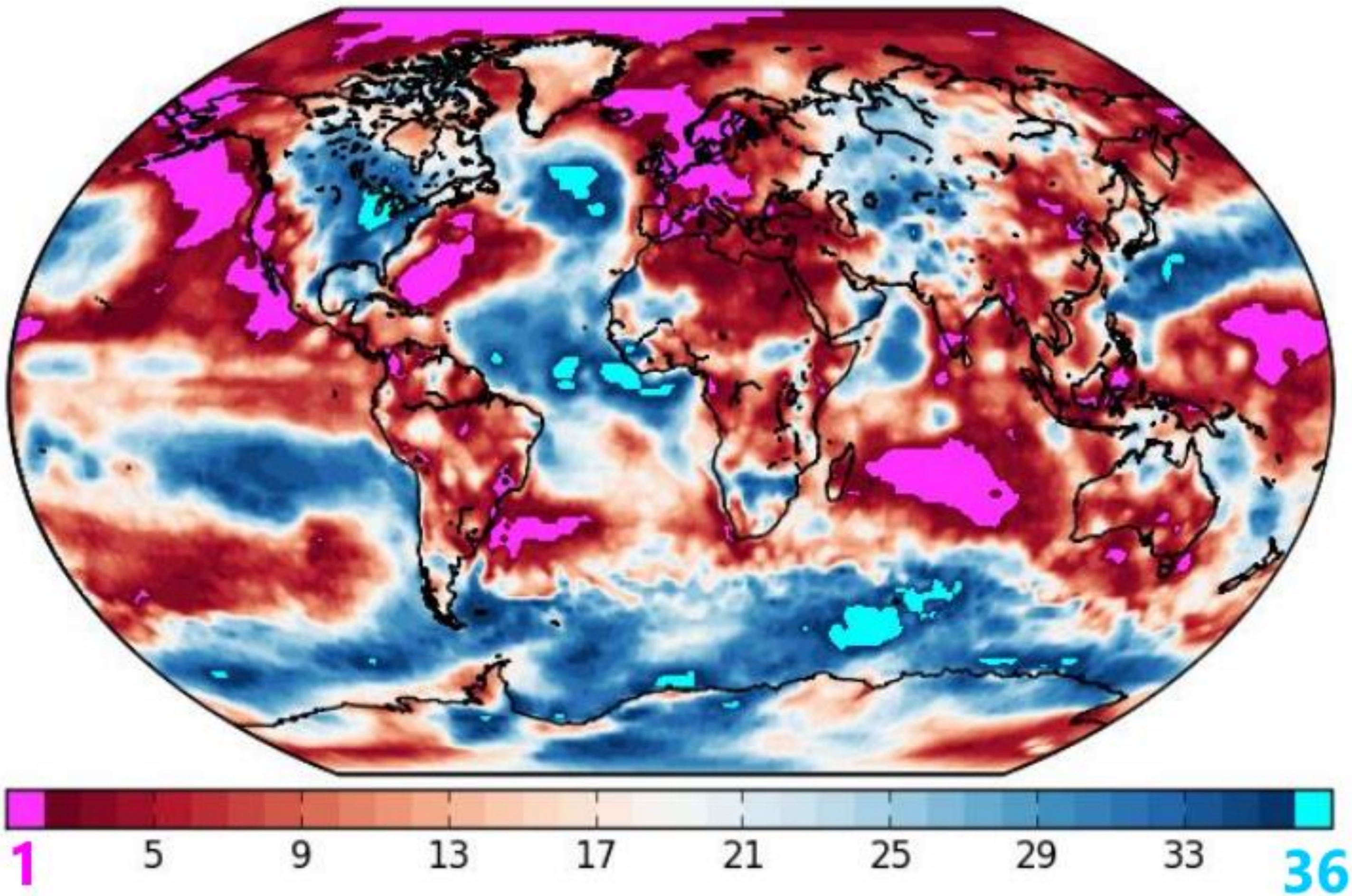
Develop user-oriented services that favour both technology transfer and adaptation

Use cutting-edge HPC and Big Data technologies for the efficiency and user-friendliness of Earth system models



2014, a special year

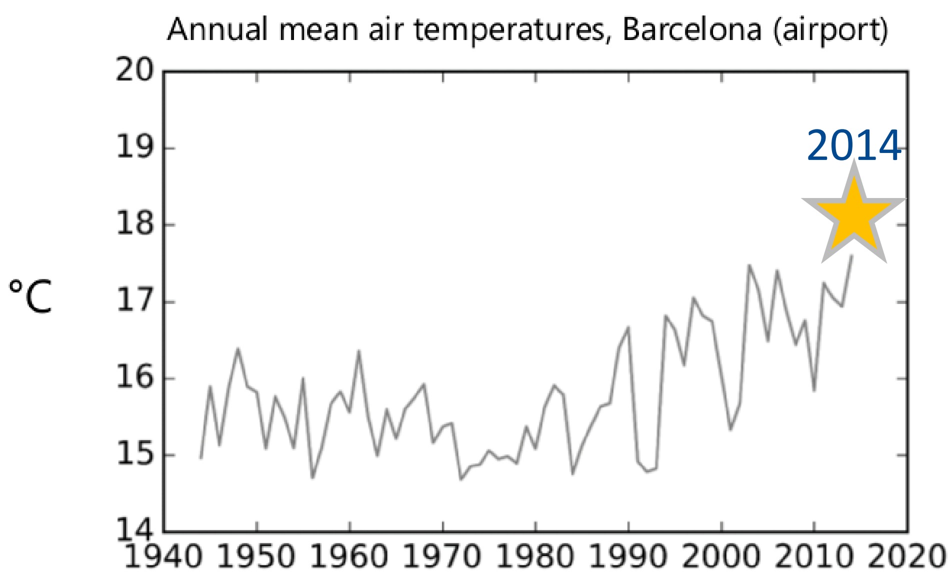
Rank of the 2014 annual mean temperature over the last 36 years from ERA Interim.

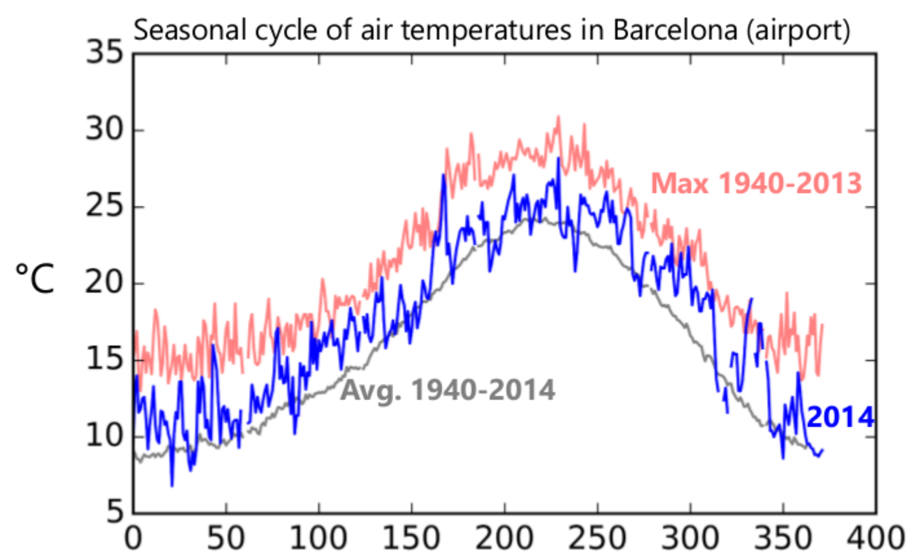


François Massonnet (IC3)

2014, a special year

Temperatures in Barcelona airport from the ECAD dataset.

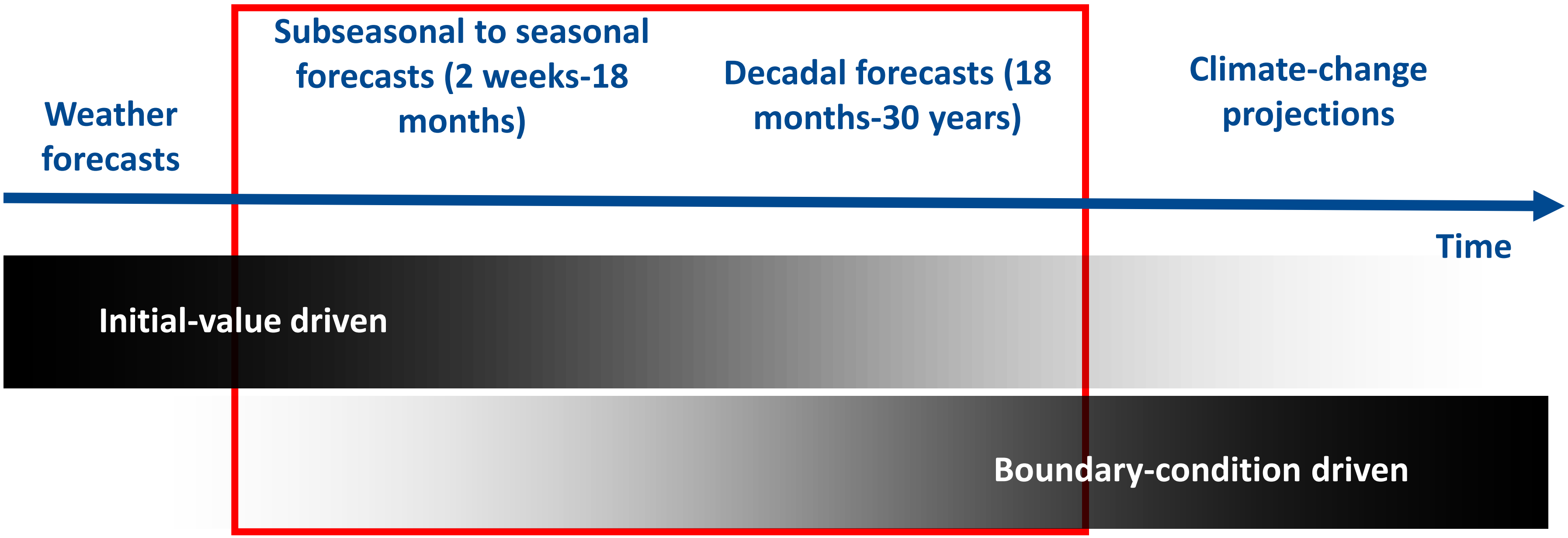




François Massonnet (IC3)

Climate prediction time scales

Progression from initial-value problems with weather forecasting at one end and multi-decadal to century projections as a forced boundary condition problem at the other, with climate prediction (sub-seasonal, seasonal and decadal) in the middle. Prediction involves initialization and systematic comparison with a simultaneous reference.

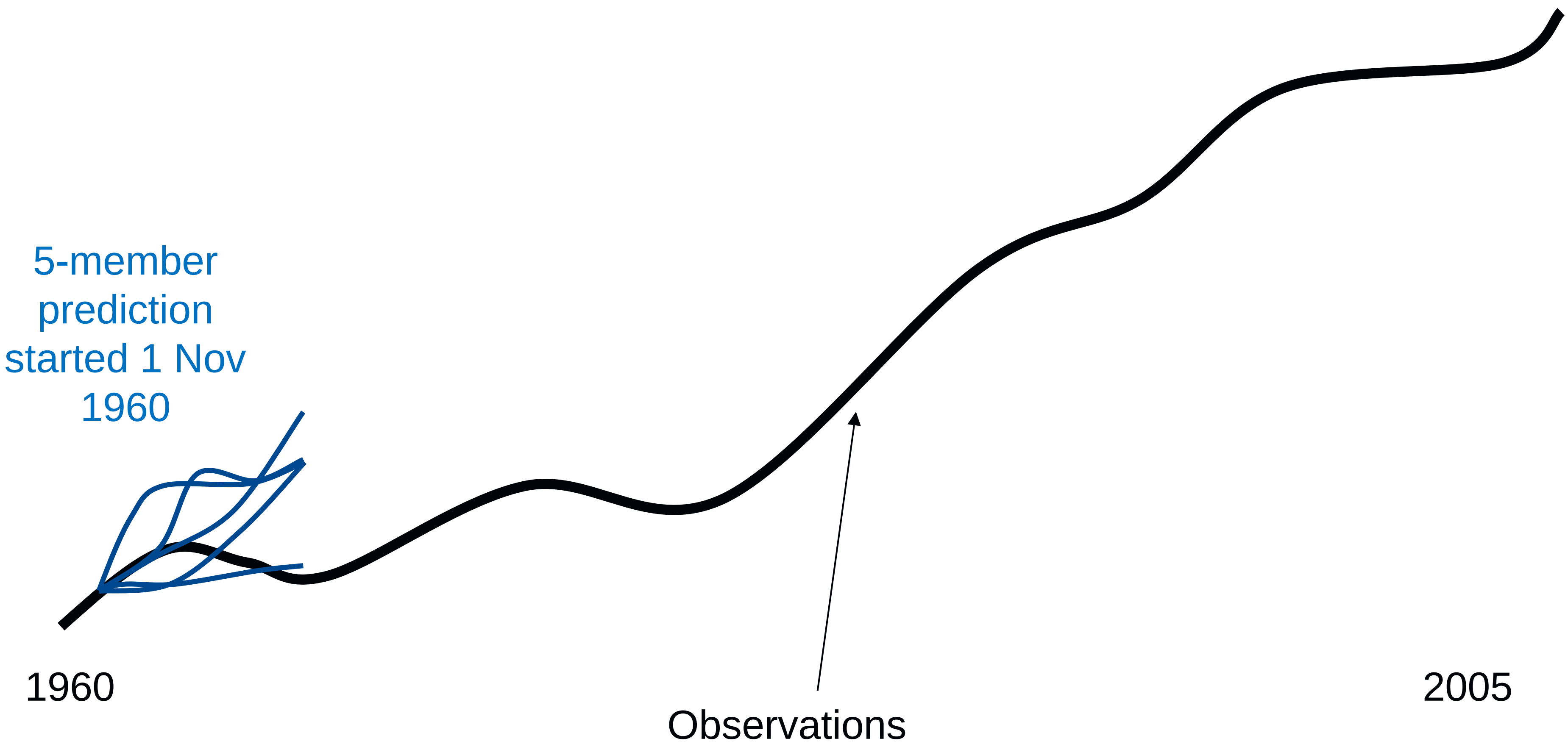


Adapted from Meehl et al. (2009)

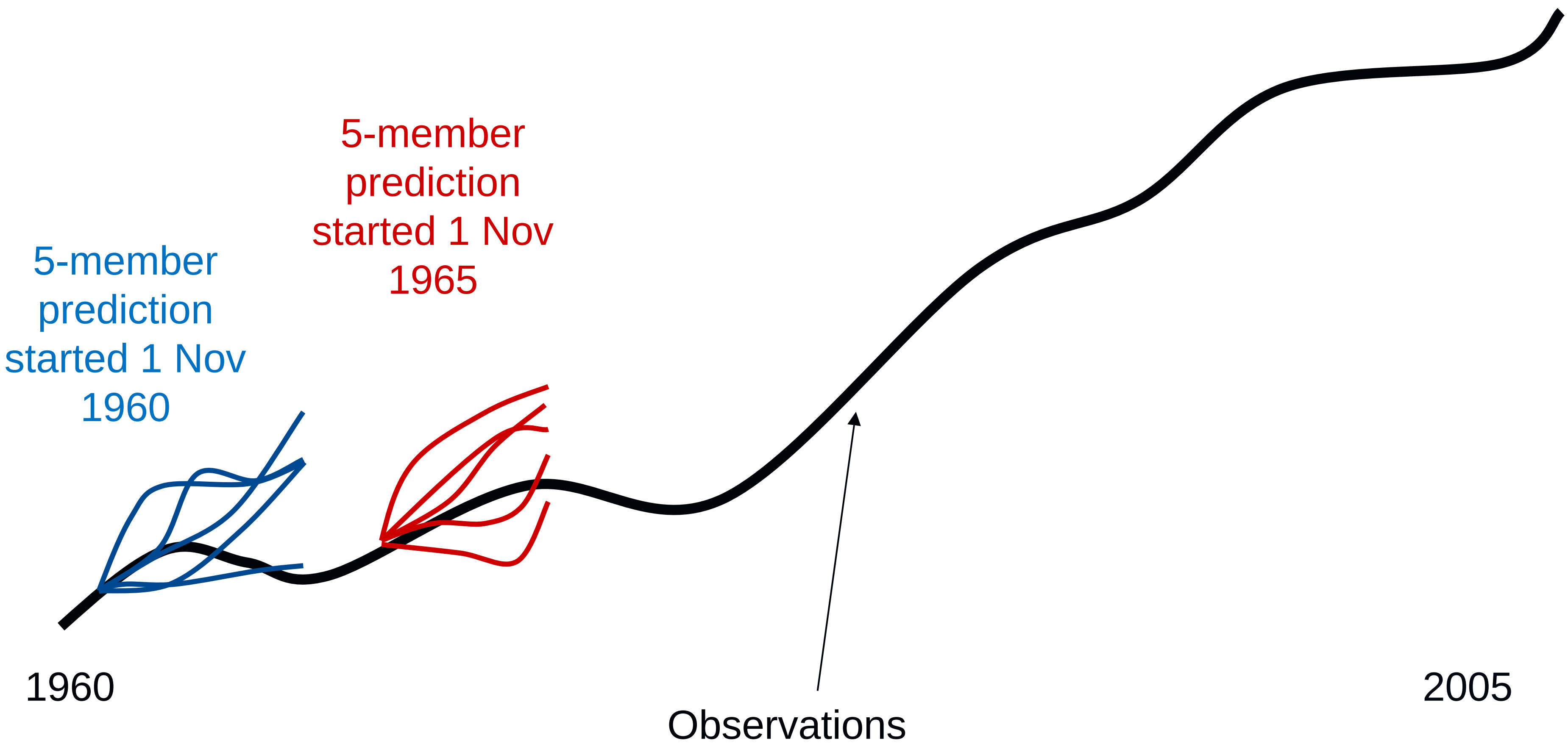
Initialising climate predictions

- Why initialising a climate model? To address the internal variability uncertainty source and make a skilful forecast, one of the requirements is an accurate knowledge of the initial state of the system.
- Steps to initialise an ensemble climate forecast system:
  - make the most of the available observations to rebuild the best estimate of the system state (reanalysis).
  - transfer such information to the model avoiding imbalances, i.e. initialise the climate prediction system
  - run the ensemble with initial perturbations to account for the initial-state uncertainty

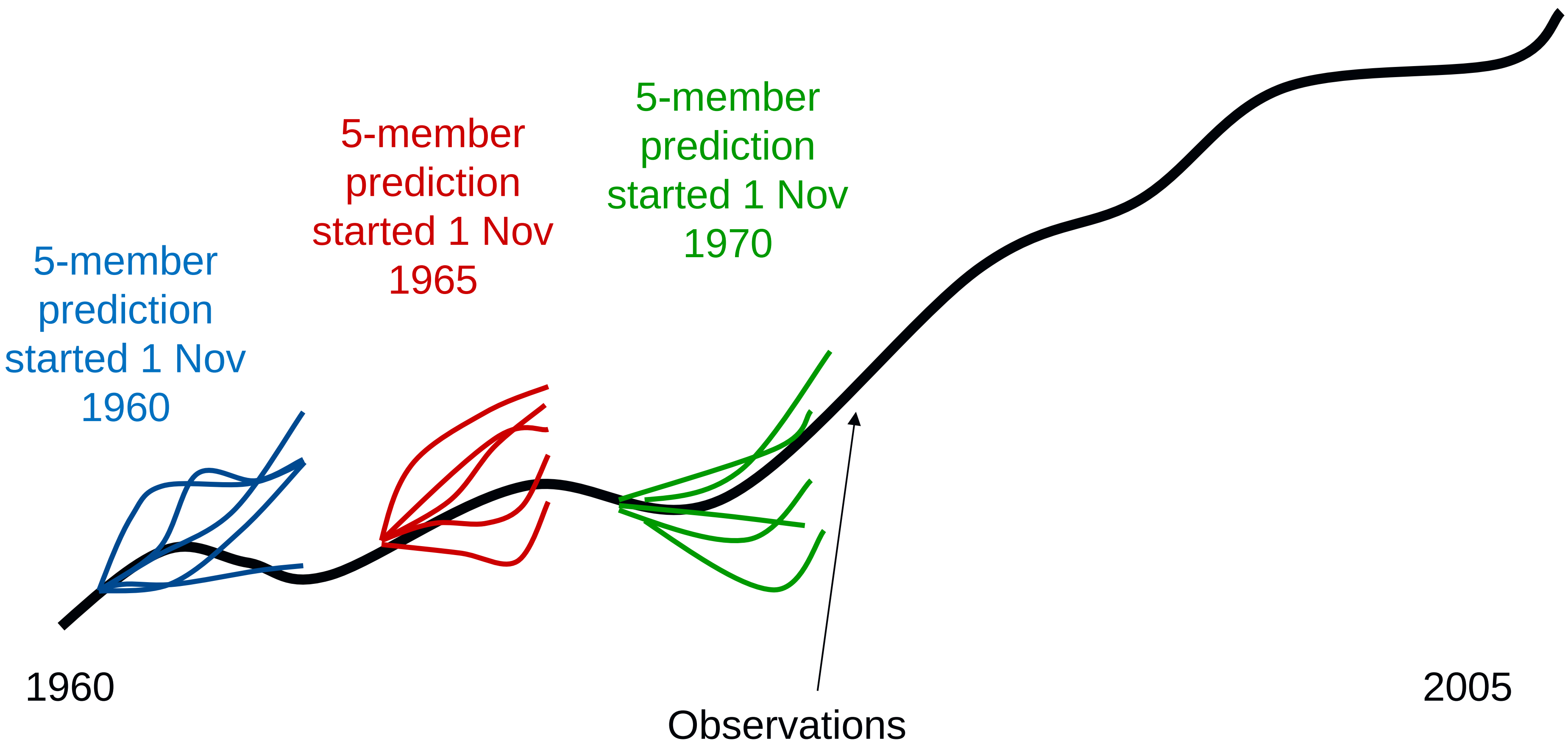
Climate prediction experiments



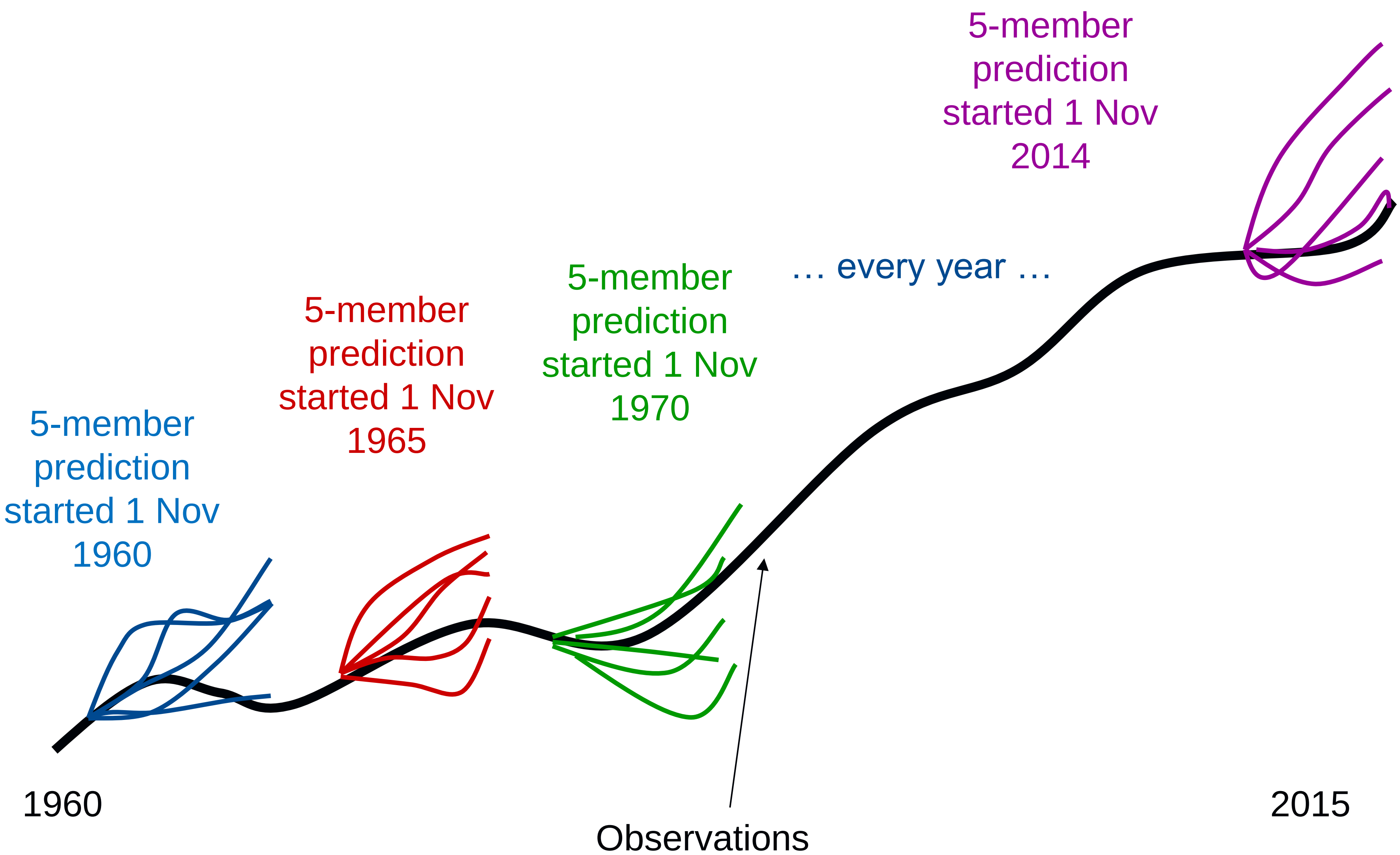
Climate prediction experiments



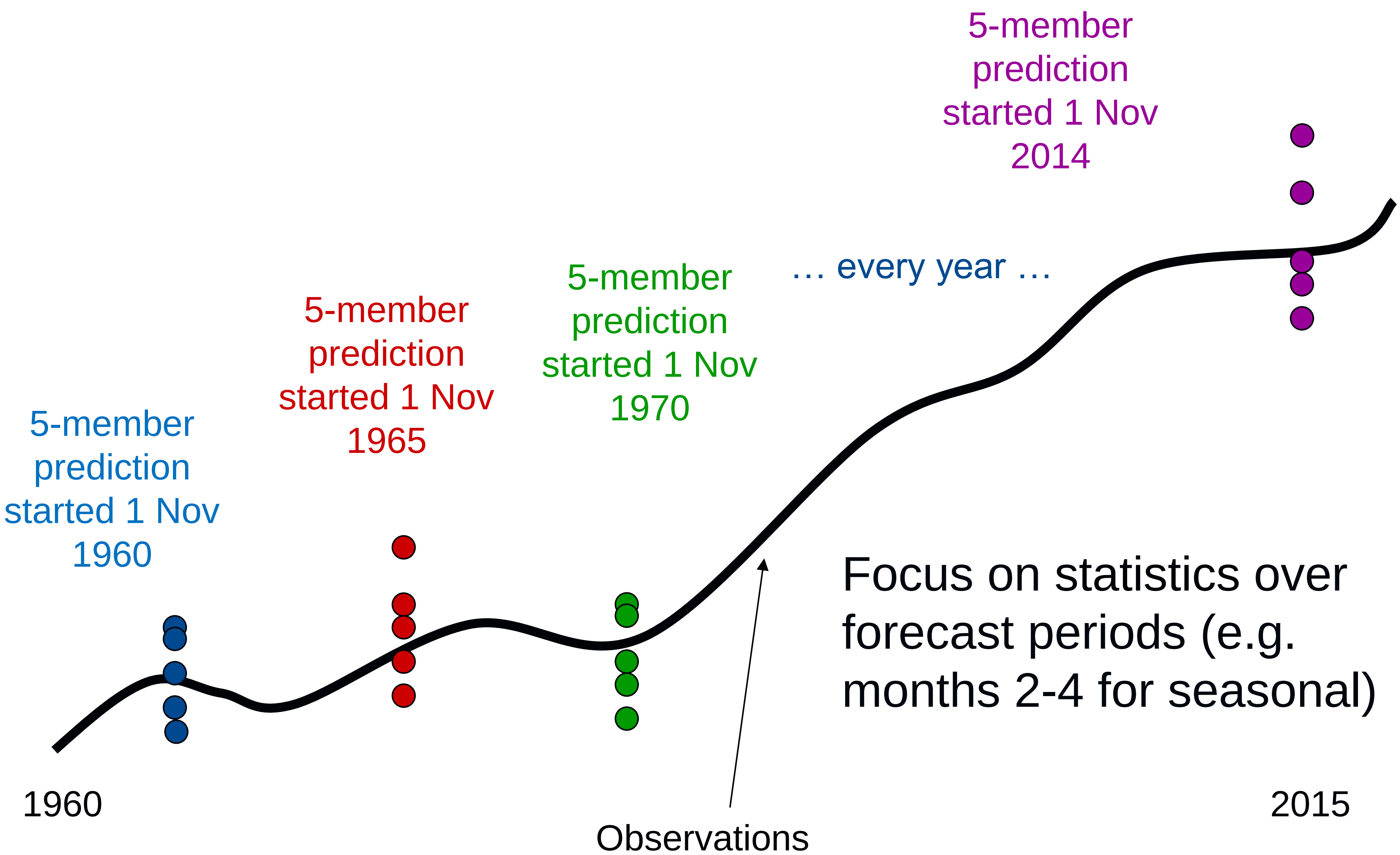
Climate prediction experiments



Climate prediction experiments



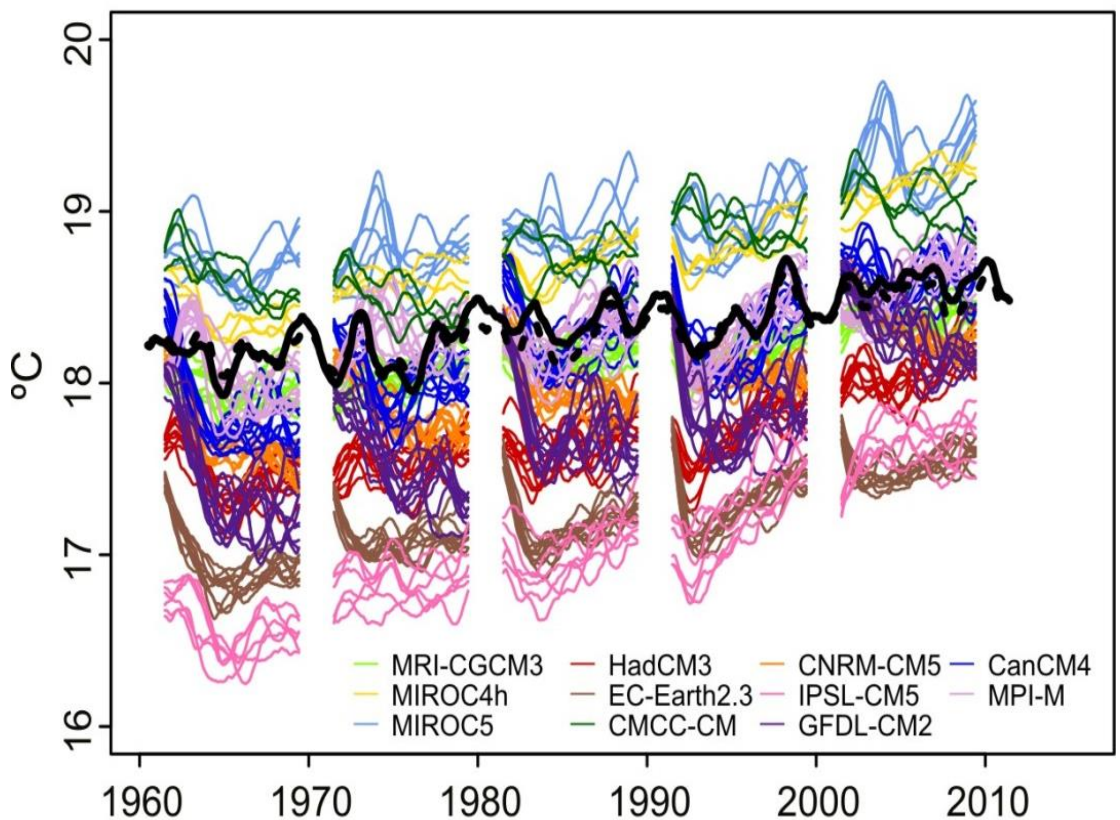
Climate prediction experiments



Systematic errors in climate prediction

Global mean near-surface air temperature over the ocean (one-year running mean applied) from CMIP5 hindcasts. Each system is shown with a different colour. NCEP and ERA40/Int used as reference.

Shock and drift is the norm.



IPCC AR5 WGI (2013)

What to predict with s2d simulations

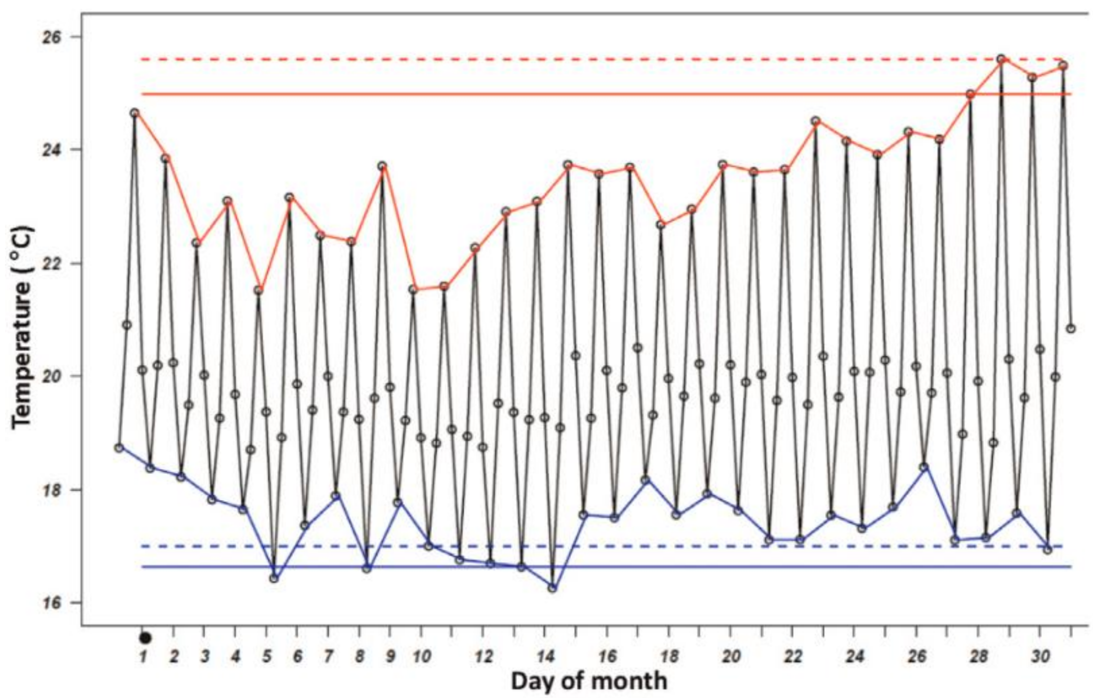
- The highest or lowest value over a period (a month, season or year).
- Relatively extreme percentiles of the distribution over a period.
- Percentage of time a variable is above or below a threshold.
- Periods (months, seasons, years) with anomalously high or low values with respect to their long term distribution.
- Frequency of high-impact events (e.g. cyclones).
- Unusual tendencies.

- In all cases, verification is needed and sometimes no adequate measures exist.

Predicting "extremes" within the month

ERAInt six-hourly temperature for an arbitrary month and point. Red lines indicate the daily maximum temperature and blue lines the daily minimum temperature. The dashed horizontal lines indicate the climatological 90th and 10th percentiles of daily variability, while the solid horizontal lines indicate the month's 90th and 10th percentiles.

This month has 7 cold and one warm days, while the monthly 90th and 10th percentiles are both lower than the long-term value.



Peppler et al. (2015, WCE)

Predicting “extremes” within the month

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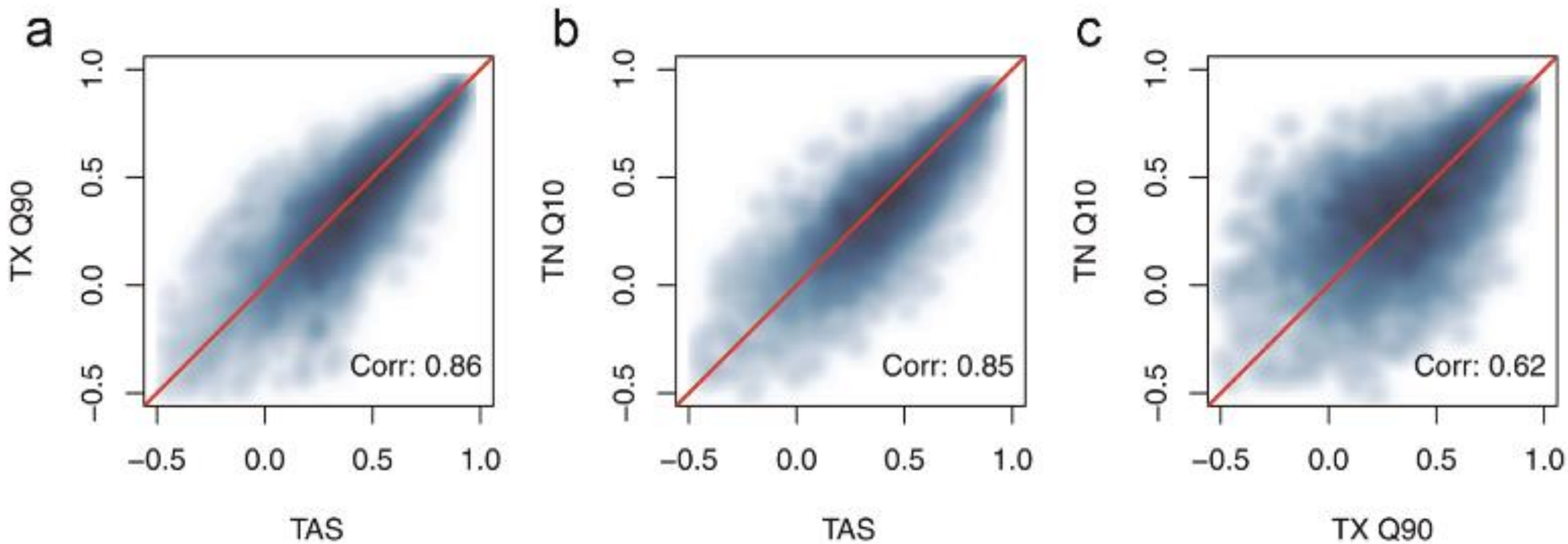
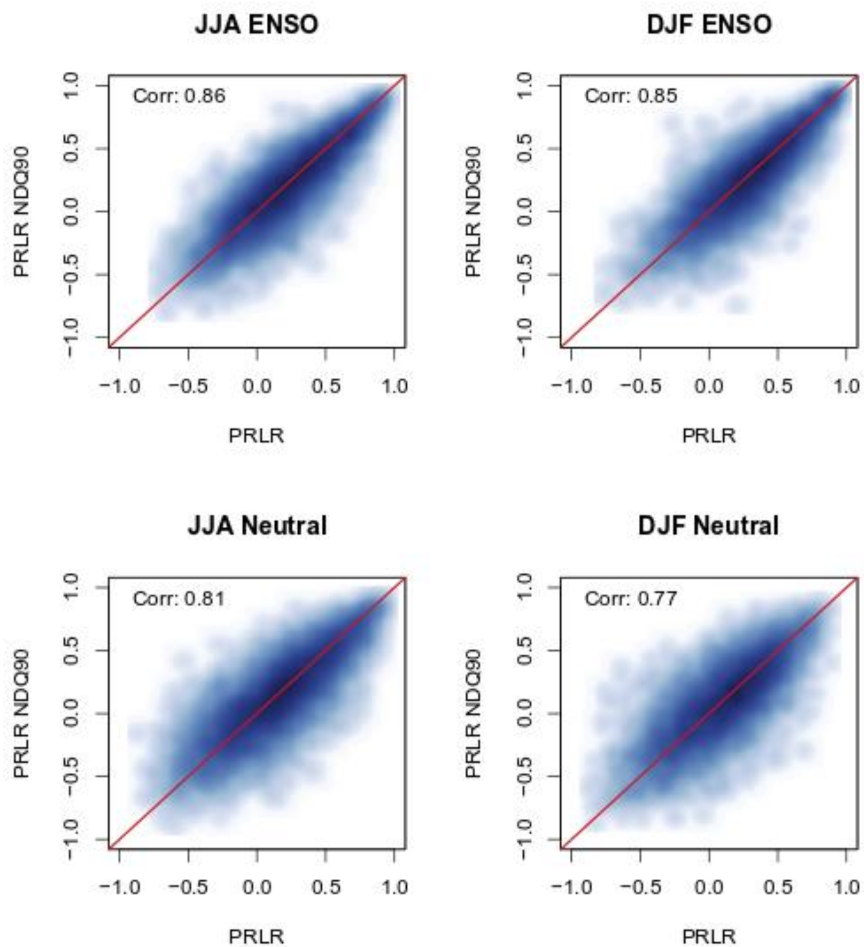
Scatter plot of the correlation of the ENSEMBLES multi-model ensemble mean for seasonal-mean daily temperature (TAS) and the 90th and 10th percentiles of Tmax (TXQ90) and Tmin (TNQ90) over the entire globe during JJA over 1979-2005. The correlation between the two samples is in the upper left corner of each panel.



Peppler et al. (2015, WCE)

Predicting "extremes" within the month

Scatter plot of the correlation of the ENSEMBLES multi-model ensemble mean for seasonal precipitation (PRLR) and the frequency of days the precipitation is above the 90th percentile (PRLRND90) over the globe during JJA over 1979-2005 stratified by the size of the ENSO anomaly.



Peppler et al. (2015, WCE)

Improving temperature forecasts

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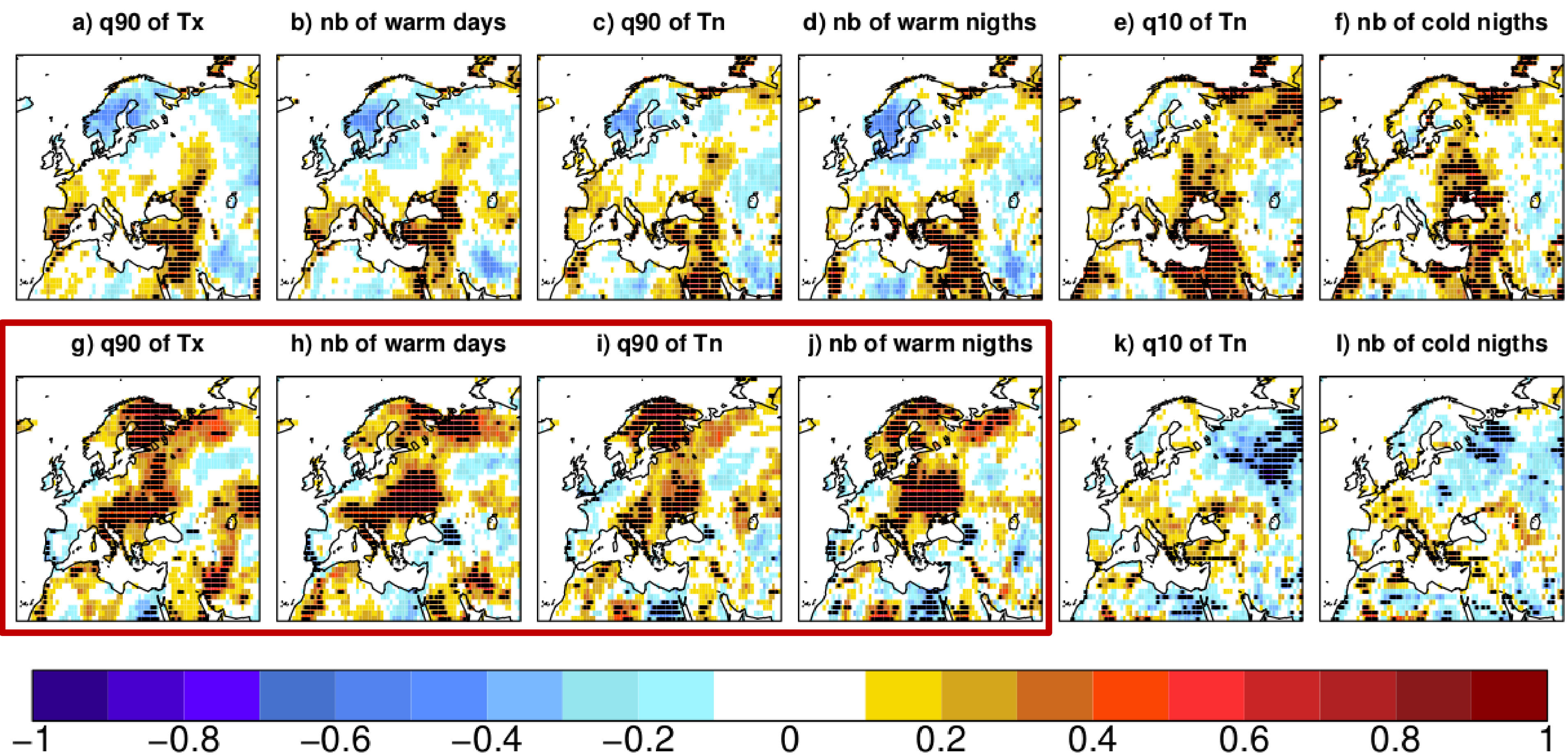
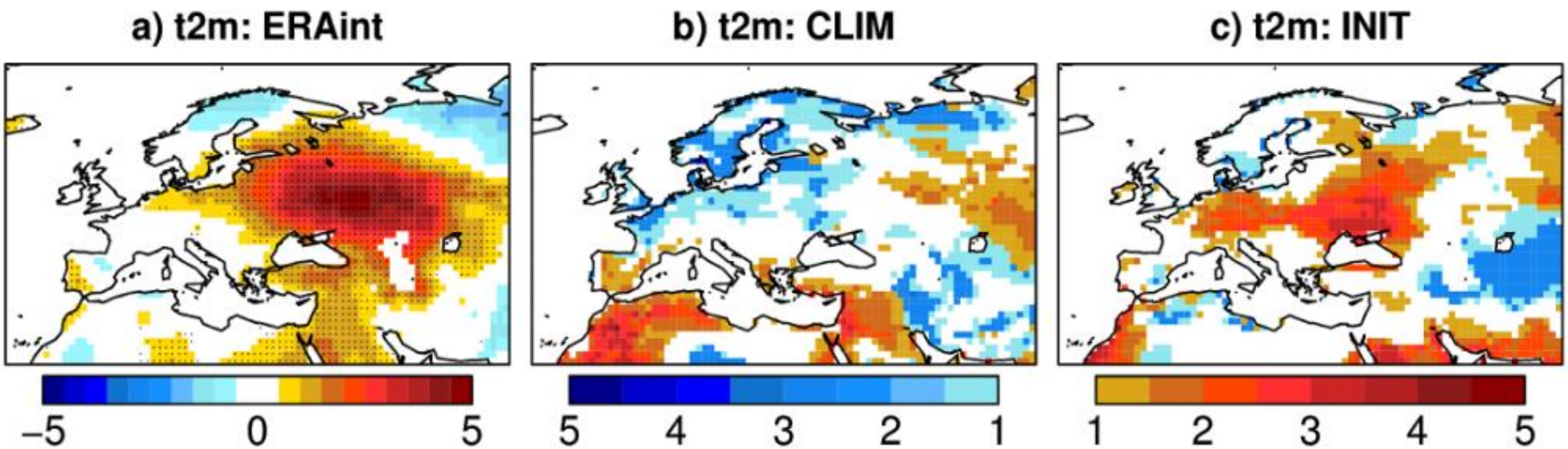
JJA near-surface temperature correlation of the ensemble mean from experiments with a climatological (top) and difference with one with realistic (bottom) land-surface initialisation. Results for EC-Earth2.3 started in May over 1979-2010.



Prodhomme et al. (2015, Clim. Dyn.)

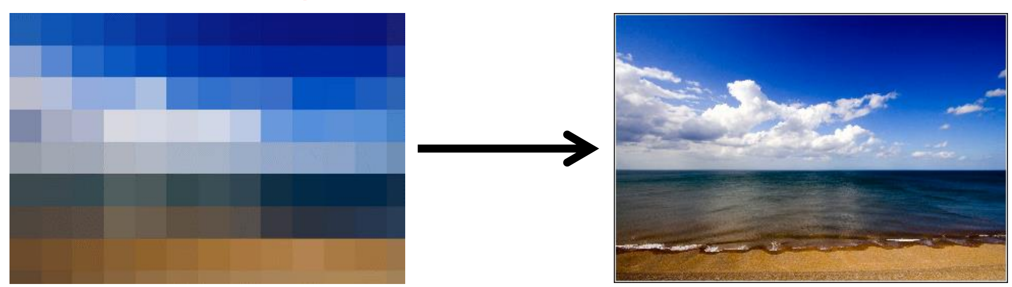
Improving temperature forecasts

JJA near-surface temperature anomalies in 2010 from ERAInt (left) and odds ratio from experiments with a climatological (centre) and a realistic (right) land-surface initialisation. Results for EC-Earth2.3 started in May with initial conditions from ERAInt, ORAS4 and a sea-ice reconstruction over 1979-2010.

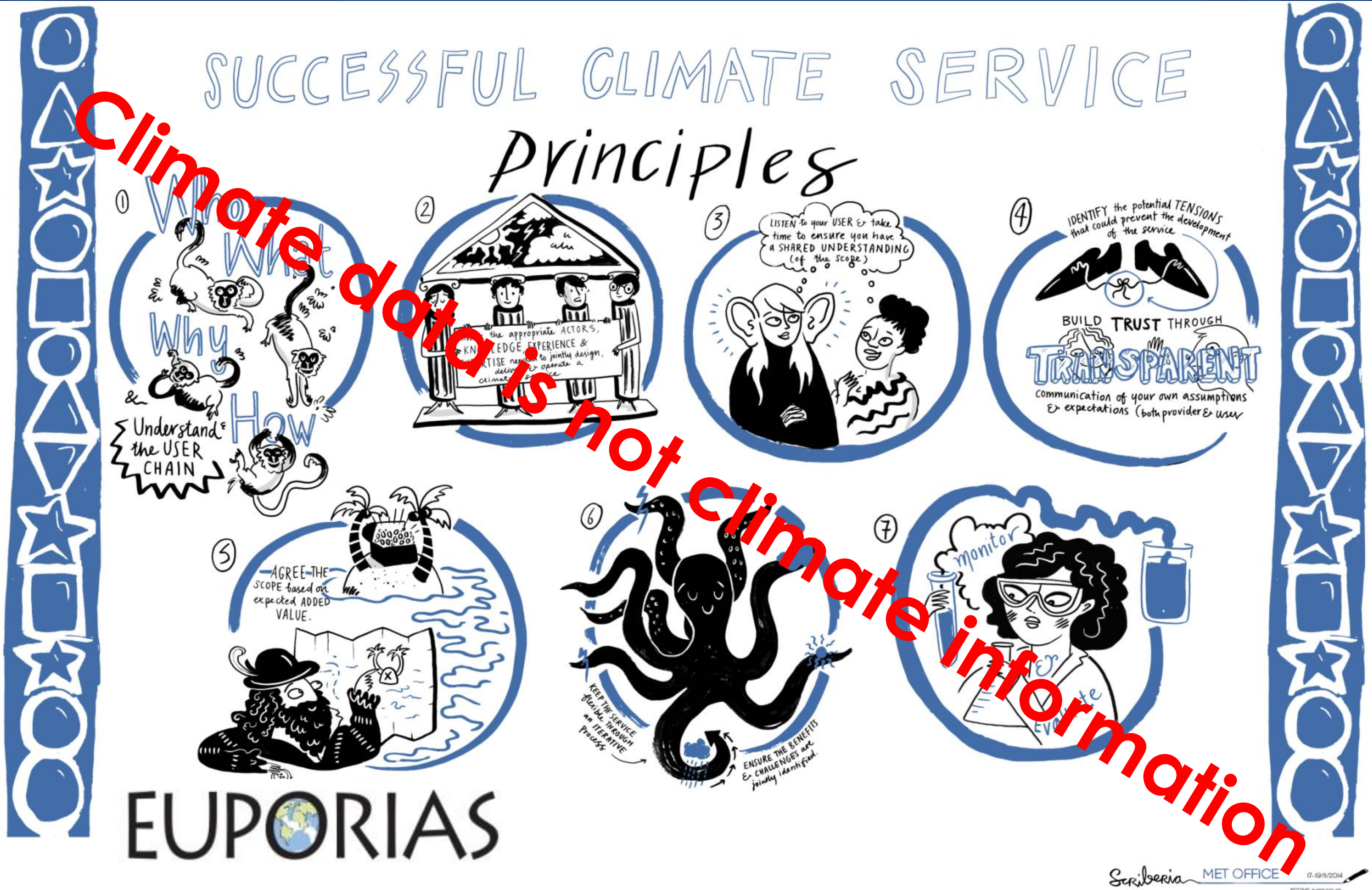


Similar results found for EC-Earth3 and high resolution (25 km).

Prodhomme et al. (2015, Clim. Dyn.)



Service-driven climate research

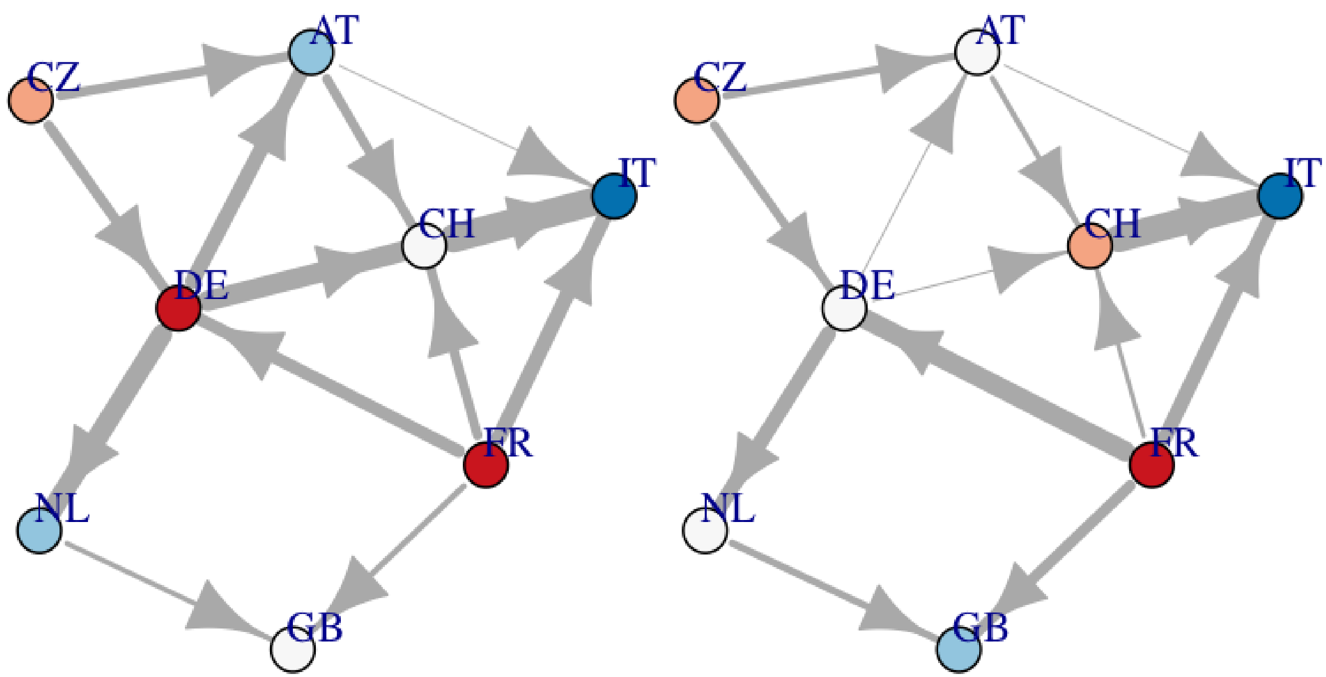


Ethical Framework for Climate Services four core elements: integrity, transparency, humility and collaboration.

Temperature forecasts for energy

European electricity flows for Jan-Feb (left) and June-July (right). Red nodes are the main exporters and blue the main importers. For clarity only the eight countries with the highest exchange are shown.

Data from ENTSO-E (2003-2014).



M. De Felice (ENEA)

Temperature forecasts for energy

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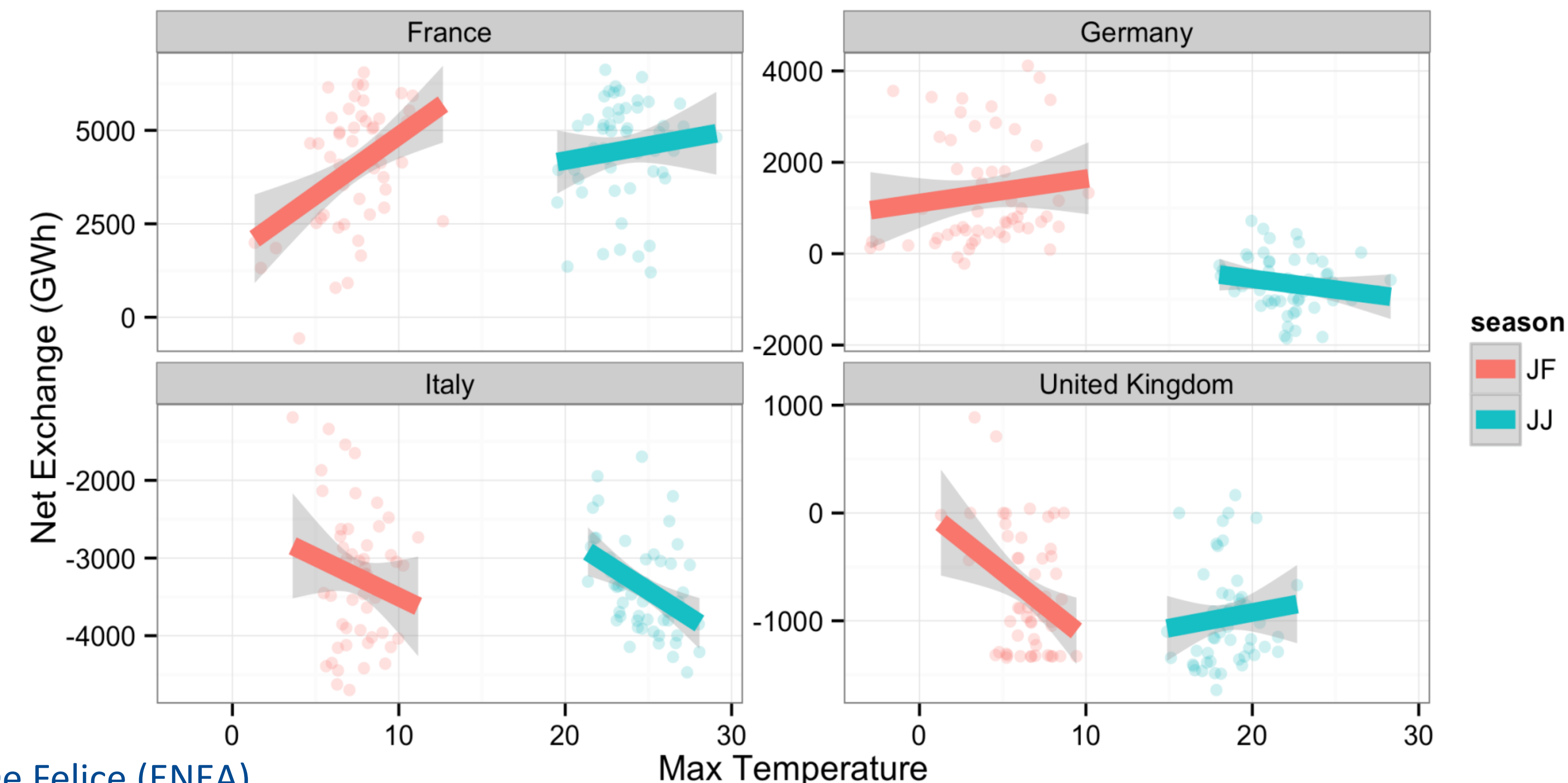
Weather and climate affect exchanges via electricity demand (heating or cooling, from the customer point of view) and RE production.

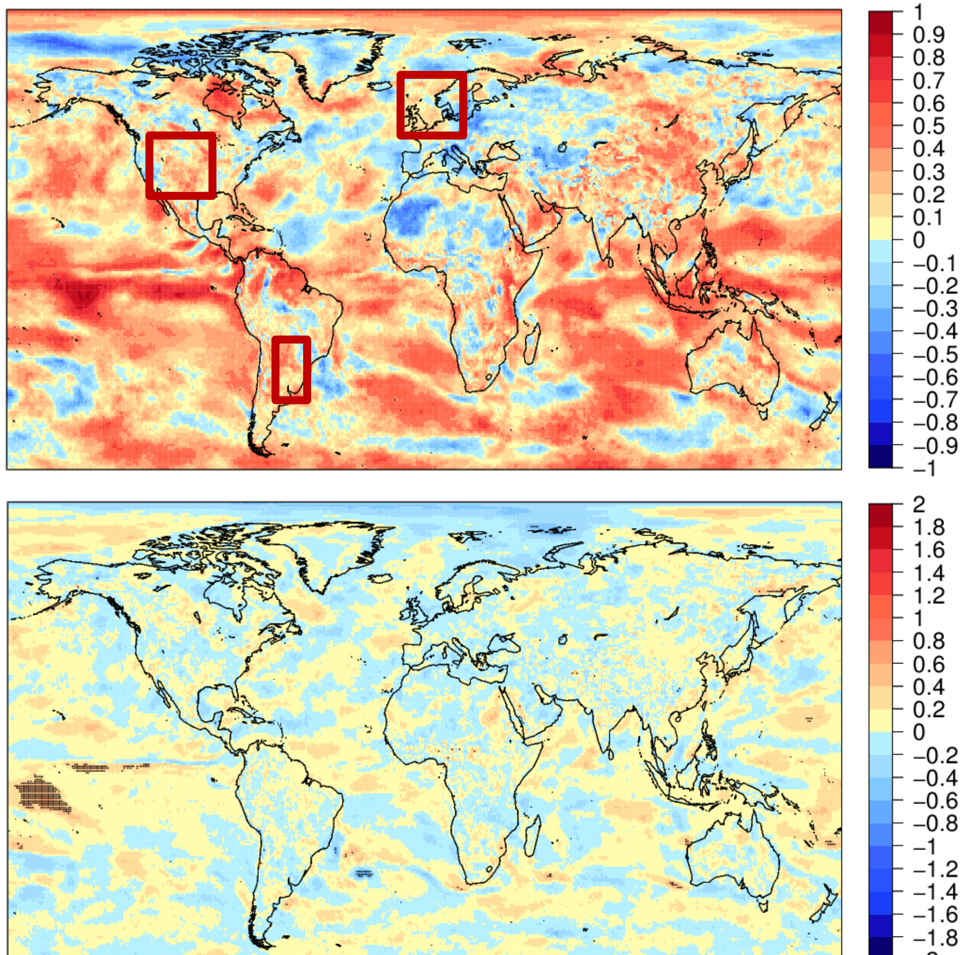
Data from ENTSO-E (2003-2014).



M. De Felice (ENEA)

Forecasts for wind energy

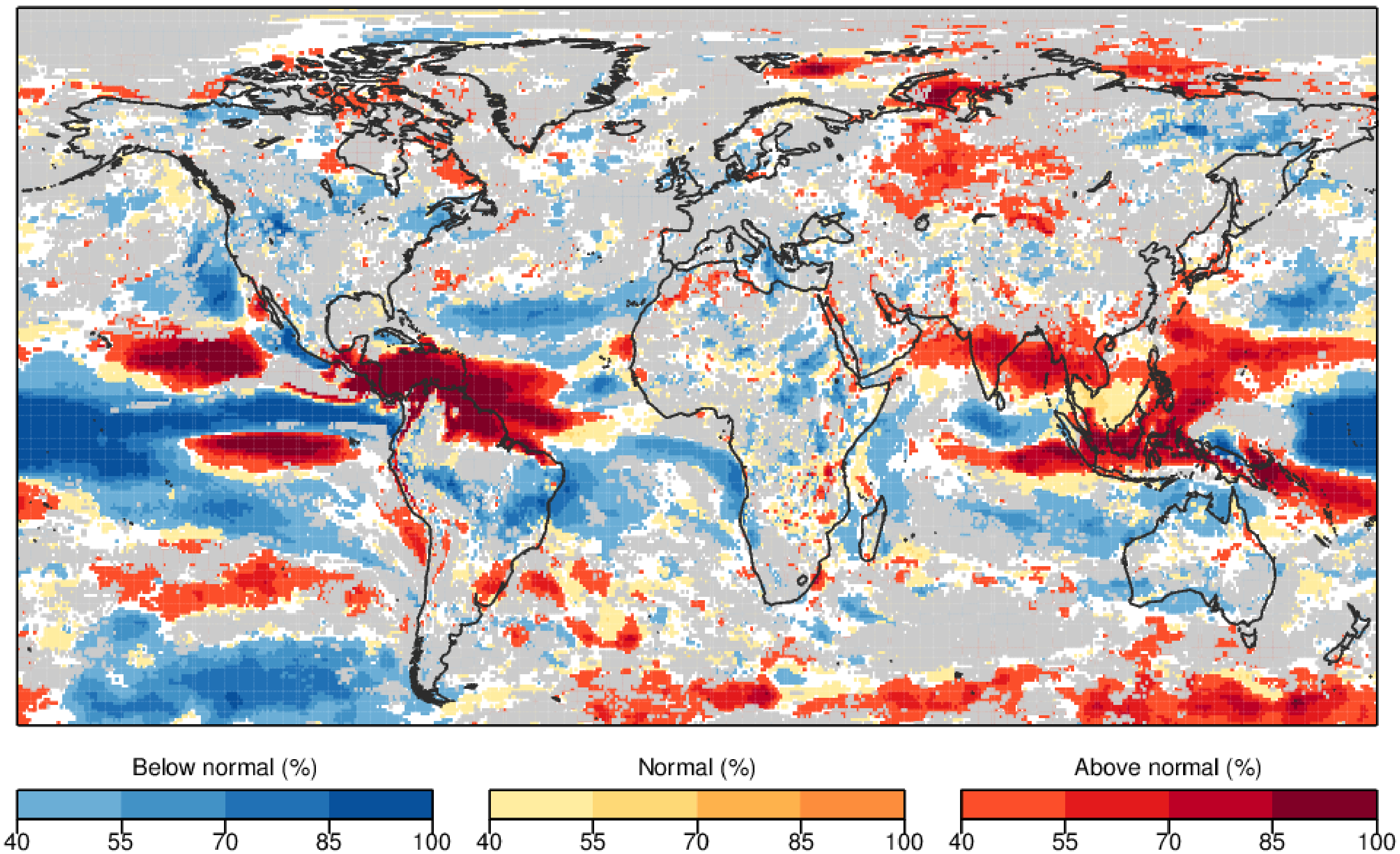
One-month lead DJF correlation of the ECMWF S4 ensemble-mean prediction of the 90th percentile of six-hourly 10-metre wind speed with ERAInt (top) and difference in correlation with the seasonal-mean wind speed (bottom) over 1981-2012.



V. Torralba (IC3)

Forecasts for wind energy

Predictions of 10-metre wind speed from ECMWF S4 for JJA 2015.

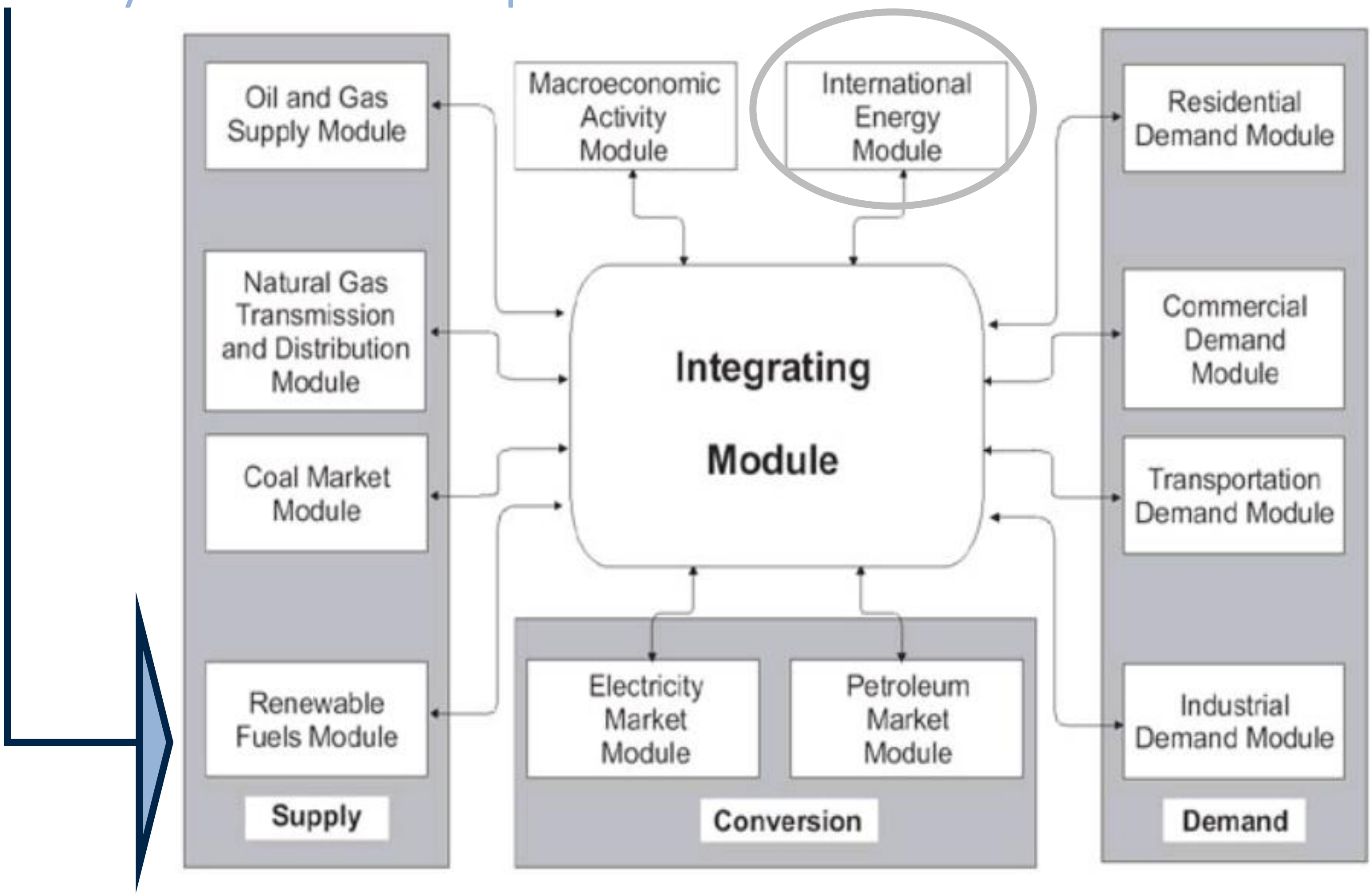


V. Torralba (IC3)

Forecasts for wind energy

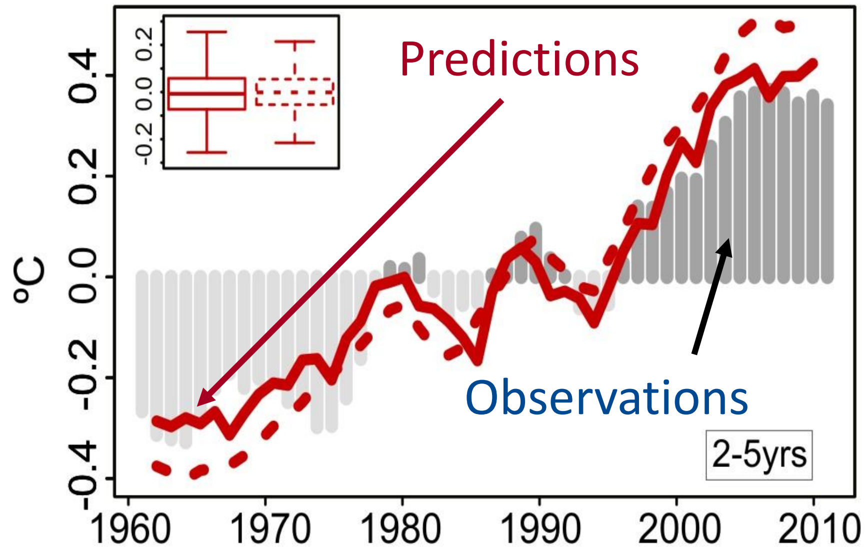
Example of a national energy model. Holistic approaches are needed.

We only addressed this part.

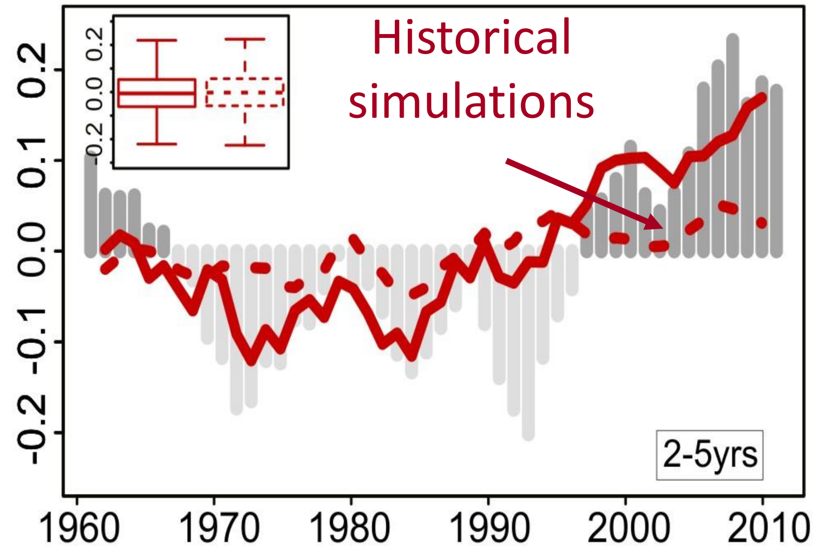


Decadal climate prediction

Global mean surface air temperature (GMST)



Atlantic multidecadal variability (AMV)



Initialised simulations reproduce the temperature trends and the AMV variability and suggest that initialization corrects the forced model response and phases in internal variability.

Doblas-Reyes et al. (2013, Nat. Comms.)

Decadal climate prediction

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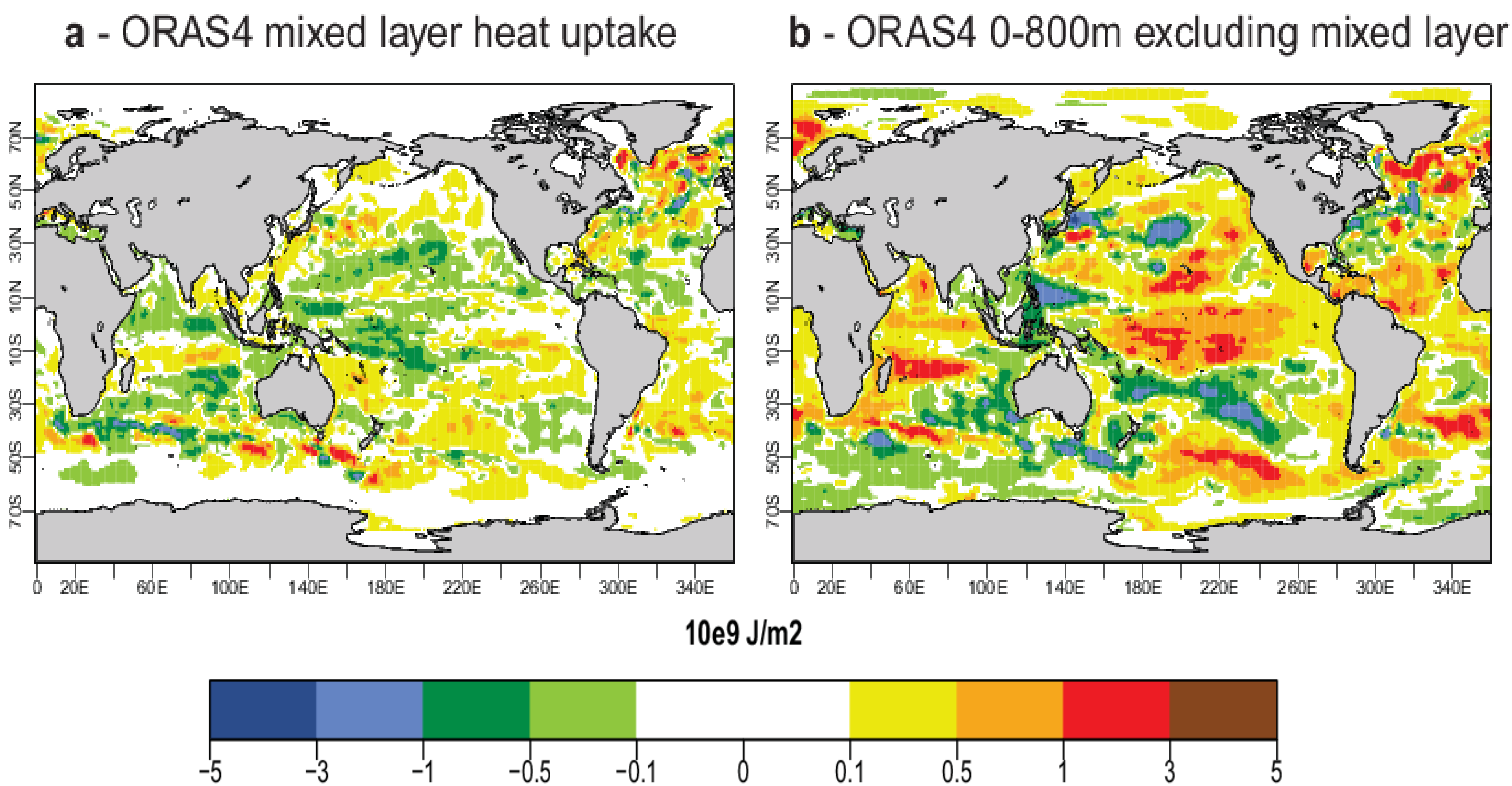
Ocean heat uptake computed as the average of the differences over the periods (2002-2005)-(1998-2001) from the ORAS4 ocean reanalysis.



Guemas et al. (2013, NCC)

Decadal climate prediction

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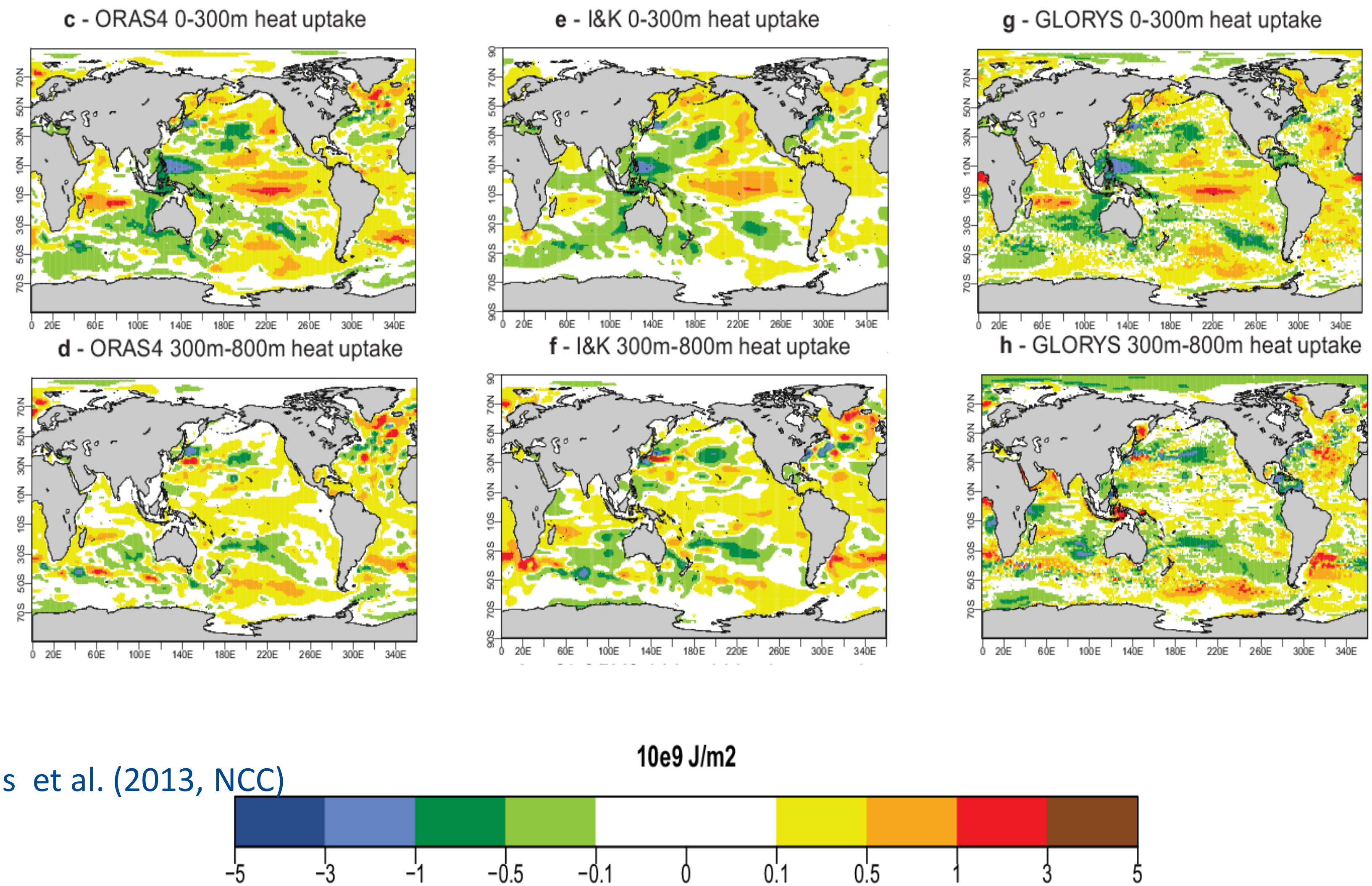

Guemas et al. (2013, NCC)

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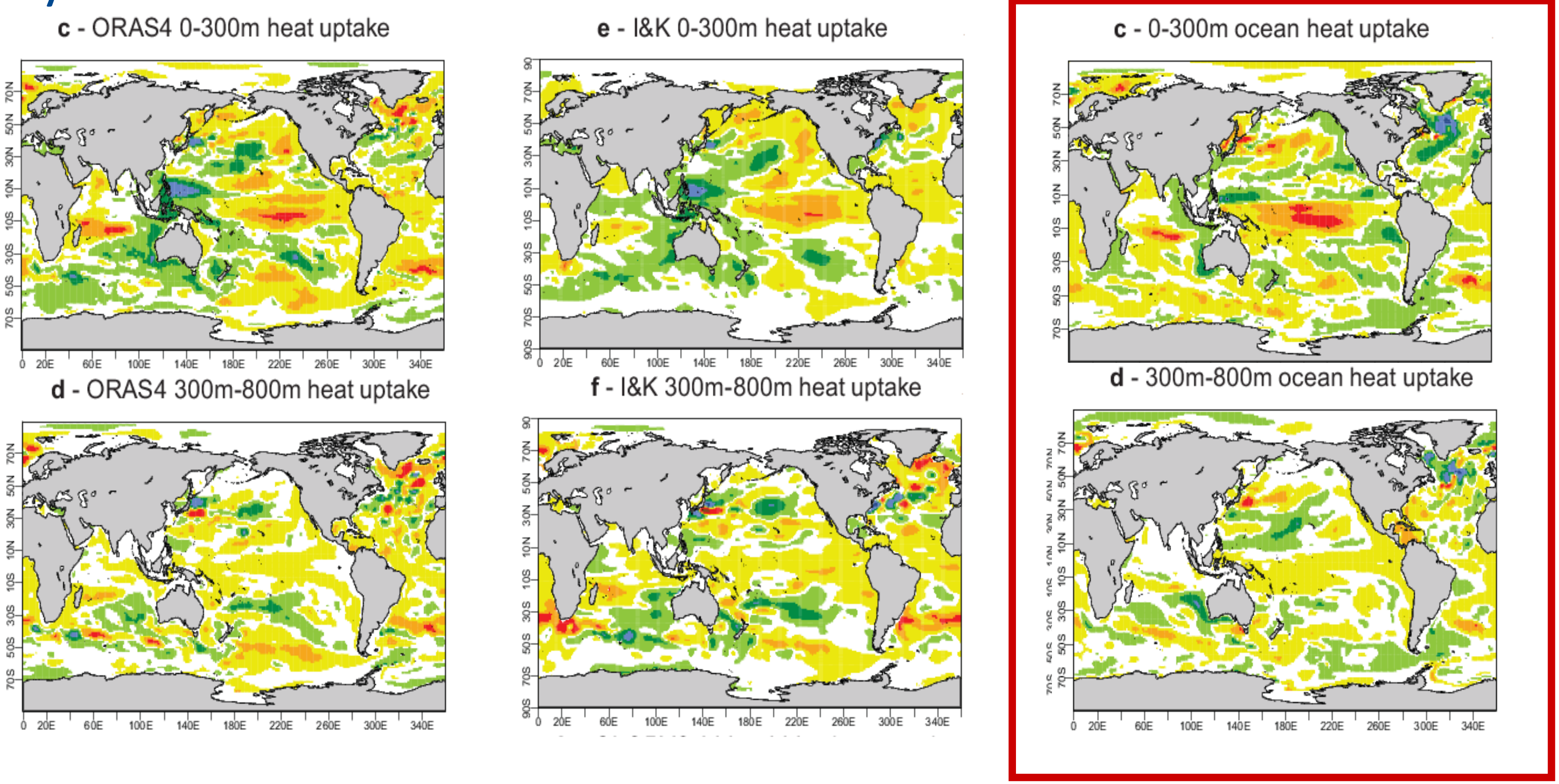
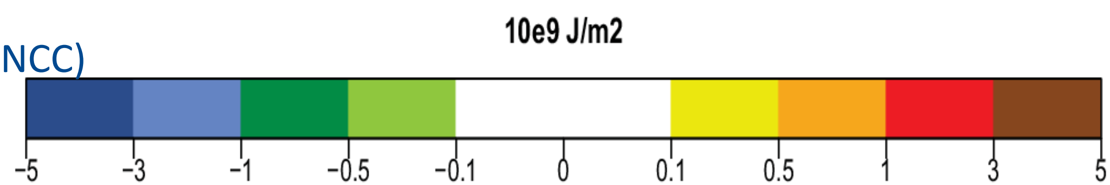


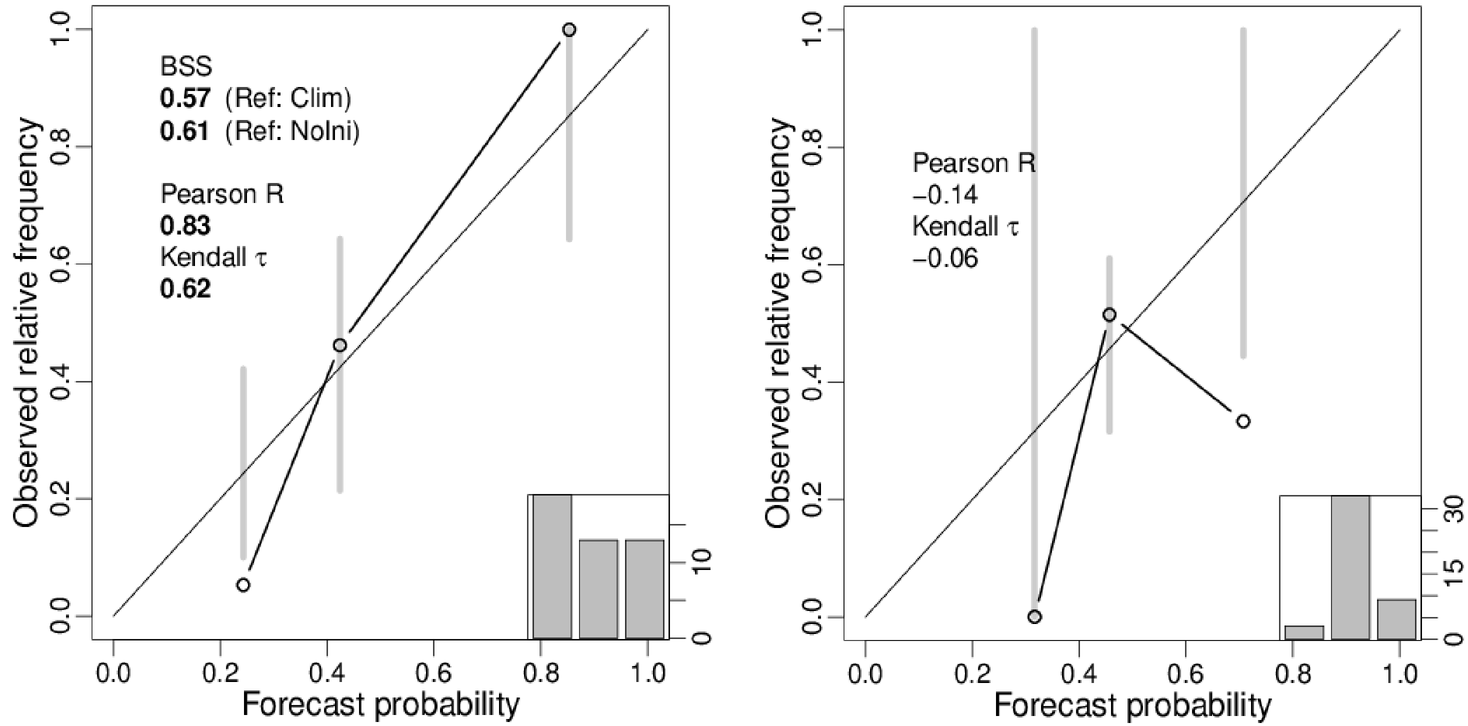
Guemas et al. (2013, NCC)



Service-driven decadal predictions

Reliability diagrams of (left) initialised and (right) uninitialised MME simulations for basin-wide **accumulated cyclone energy** (ACE). The results are for 2-9 year averages above the climatological median over 1961-2009. Statistically significant values are in bold.

Some of the added value of the predictions is their better management of uncertainty, which leads to increased **credibility**.

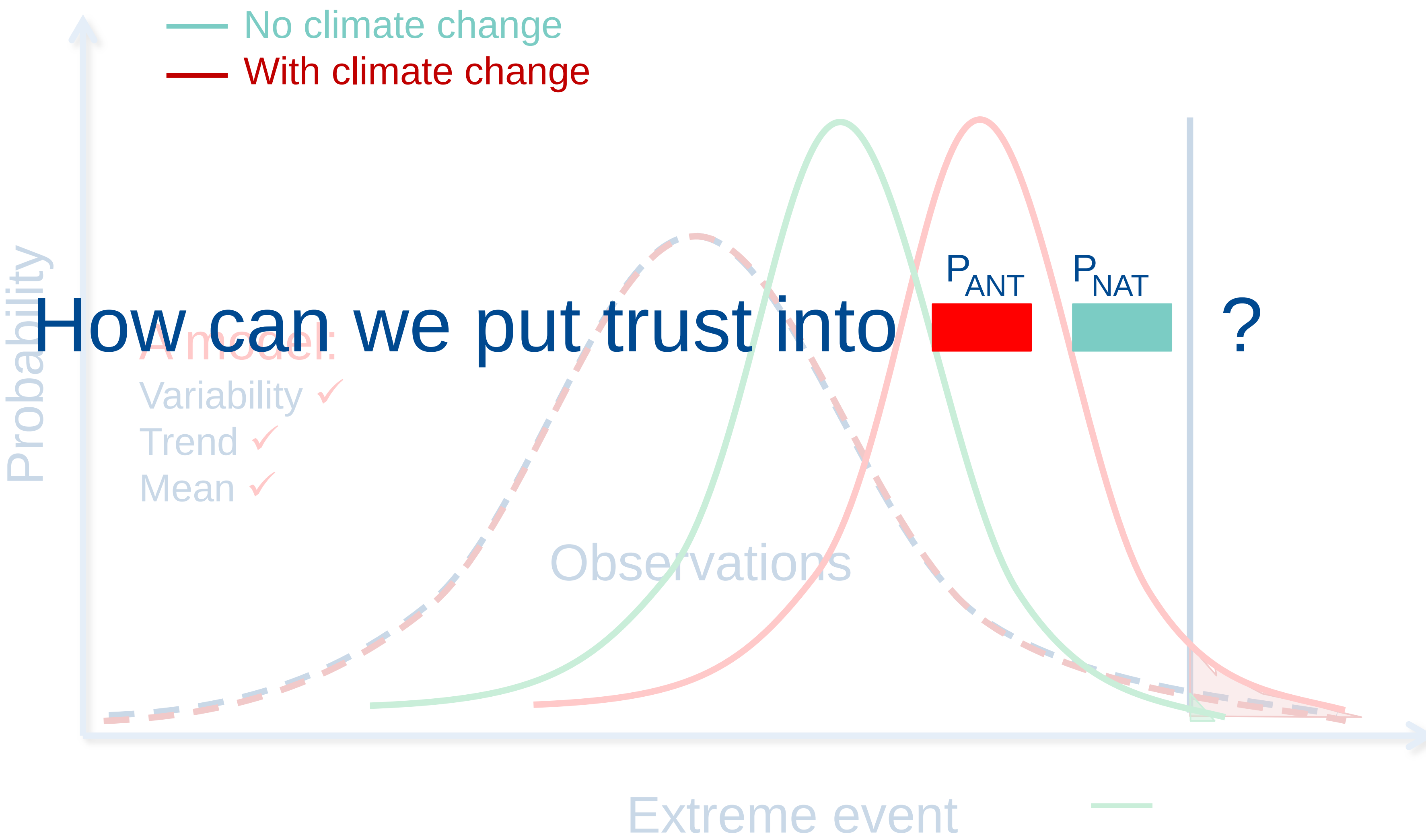


Caron et al. (2015, GRL)

Interpreting reliability

- Probability enables honest communication with end user and better decisions.
- Reliability: if the probability of an event y is q the event should happen on average q 100% of the times $P(y=1|p=q)=q$.
- The reliability diagram is a plot of $P(y=1|p)$ over p. Pointwise consistency bars by resampling and histogram of probabilities (sharpness diagram) should be added.
- The rank histogram verifies the raw ensemble, independent from the method used to obtain the probabilities, and measures whether the ensemble and the observation come from the same underlying distribution. It requires exchangeability and would benefit from testing for alternatives to flatness.

Event attribution and reliability



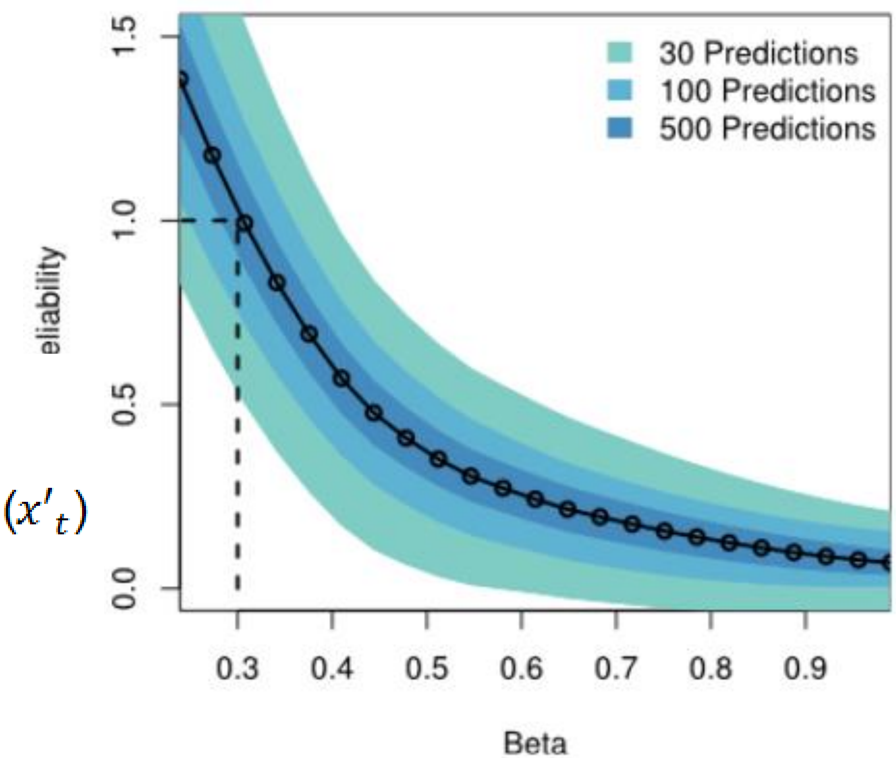
How can we put trust into P_{ANT} P_{NAT} ?

Event attribution and reliability

Simple system to create an actual and counterfactual model by setting a non-zero and zero value for *s*, respectively.

The beta parameter sets the reliability of the system and is set equally for both worlds (example with 1000 ensemble members and ratio between *s* and the residual variability of 1.5).

$$x_t = x'_t + st$$
$$x'_t \backsim N(0, \sigma_x = 1), t \in [0, T]$$
$$F_t = \alpha x'_t + \epsilon_\beta + st + (\epsilon_1, \ldots, \epsilon_M)$$
$$\epsilon_\beta \backsim N(0, \beta)$$
$$\epsilon_{1,\ldots,M} \backsim N(0, \sigma_M = \sqrt{(\sigma_x - \alpha^2 - \beta^2)}$$



s slope of the linear trend

F_t synthetic forecast

α predictable fraction of the observed anomaly (x'_t)

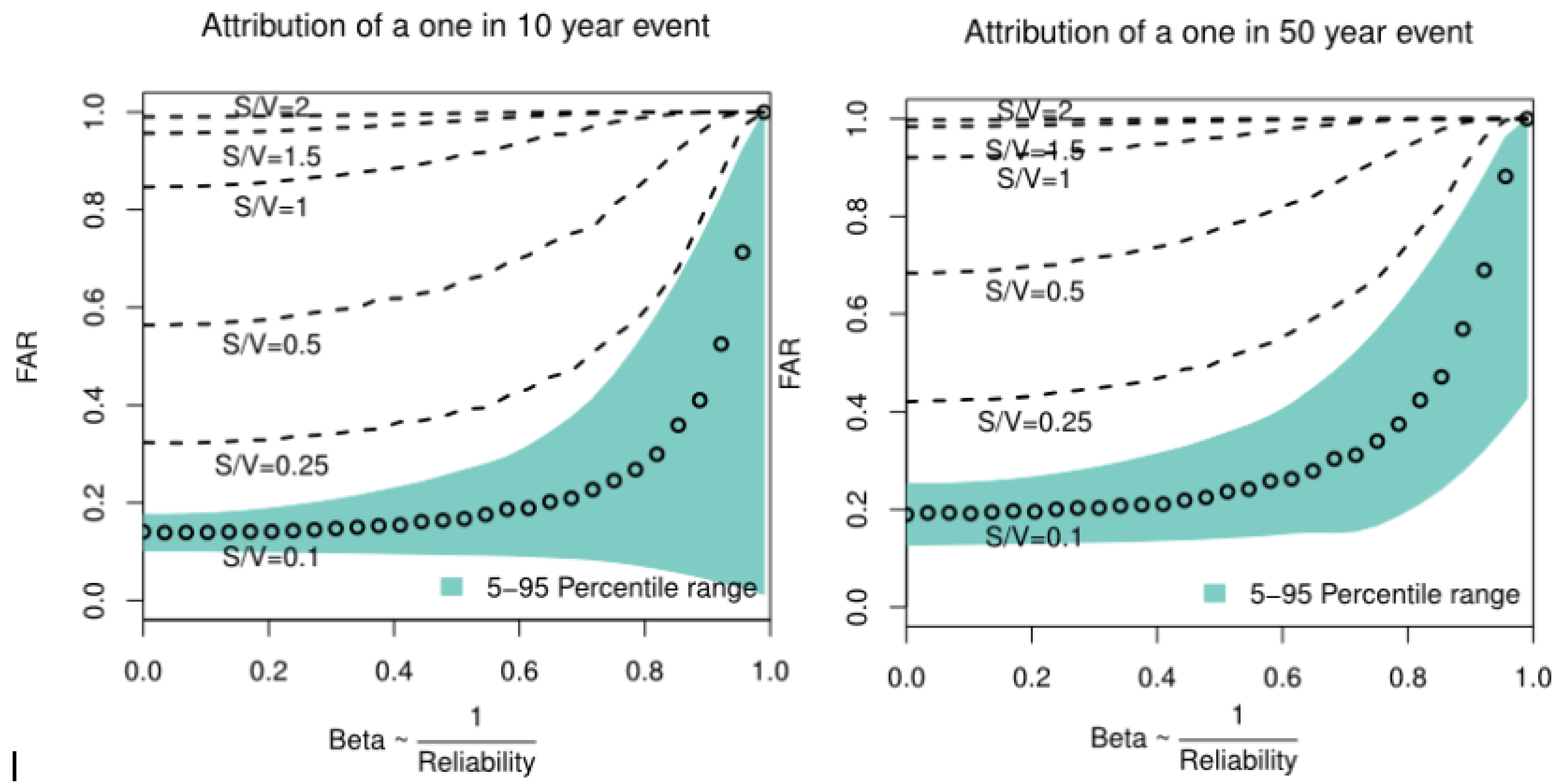
β standard deviation of the forecast error (ϵ_β)

M ensemble size

Bellprat and Doblas-Reyes (submitted)

Event attribution and reliability

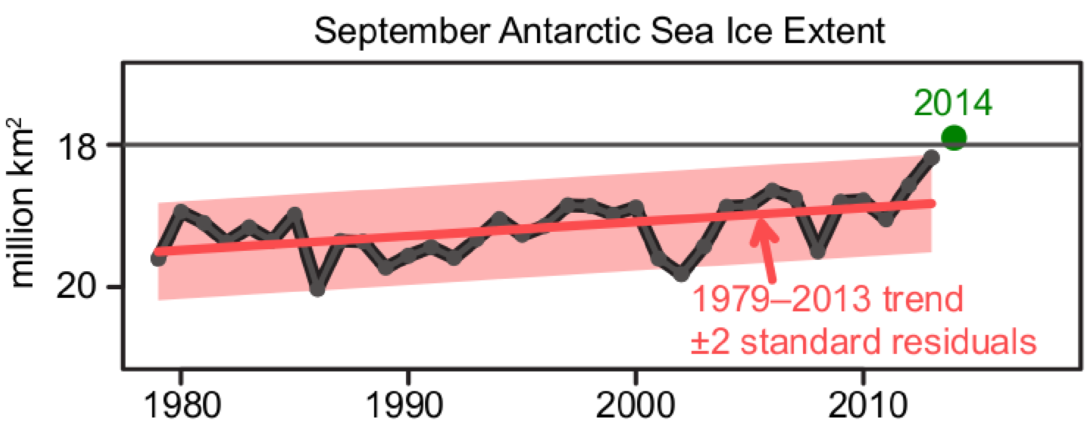
Relationship between FAR and reliability. A positive bias exists in unreliable systems with low ratio of signal to interannual variability. There is also large uncertainty in the FAR values.

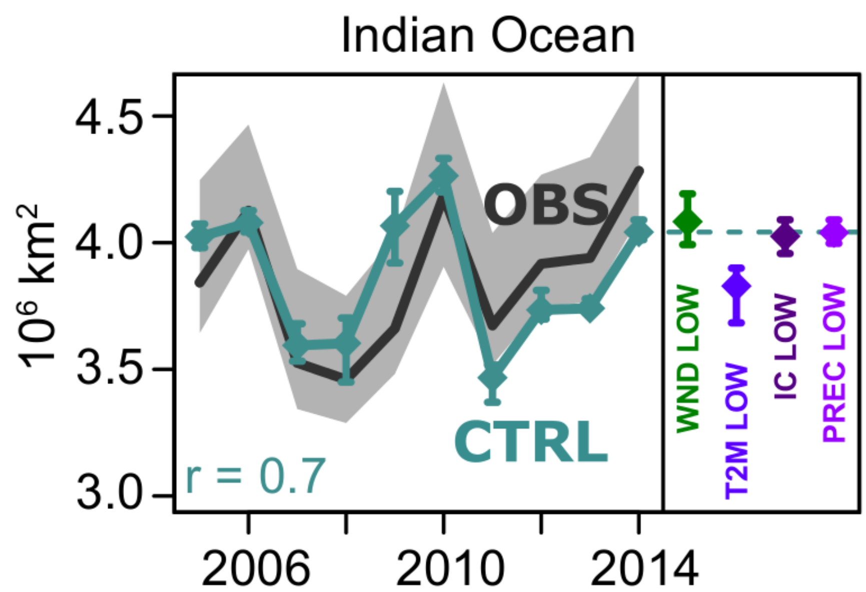


Bellprat and Doblas-Reyes (submitted)

Event attribution

2014 was an exceptional year for the Antarctic sea-ice extent. A set of sensitivity experiments with NEMO allows to attribute it to anomalous southerly advection of cold air (Indian sector) and ocean pre-conditioning (Ross Sea).





Massonnet et al. (2015, BAMS)

Summary

- Requests for climate information for the next season comes from a broadening range of users and should be addressed from a climate services perspective. What forecasters provide is still far from what some users demand (even in the absence of skill) and is only part of a complex story.
- Land-surface initialisation increases the forecast quality in the midlatitudes, including a range of extreme measures.
- Decadal prediction shows signs of providing useful information for some extreme events.
- Models still have substantial errors that need to be understood and communicated. Forecasts also have to deal with the drift.
- FAR in unreliable systems (valid not just for forecast systems) with low signal-to-noise ratios should be used with care as could be biased and highly uncertain.